

## Loss Minimization Control for Induction Generators in Wind Power Systems Using Support Vector Regression

Ahmed G. Abo-Khalil, Dong-Choon Lee  
Yeungnam University

**Abstract** - In this paper, a novel algorithm for increasing the steady state efficiency during light load operation of the induction generator that integrated with a wind power generation system is presented. The proposed algorithm based on the flux level reduction, where the flux level is estimated using Support-Vector Machines for regression (SVR) for the optimum d-axis current of the generator. SVR is trained off-line to estimate the unknown mapping between the system's inputs and outputs, and then is used online to calculate the optimum d-axis current for minimizing generator loss. The experimental results show that SVR can define the flux-power loss accurately and determine the optimum d-axis current value precisely. The loss minimization process is more effective at low wind speed and the percent of power saving can approach to 40%.

### 1. Introduction

In recent years, there has been a widespread growth in the exploitation of wind energy, which required the development of larger and more robust wind system [1]. In a variable speed wind energy generation system (WEGS), below the rated wind velocity, the electrical torque is controlled in order to drive the system at an optimum speed for maximum power extraction. Previous researches have focused on two major types of maximum wind power extraction, that is, the optimal tip-speed ratio (TSR)[2] and search-based control (SC)[3]. TSR control has been proposed to regulate the rotor speed of wind turbine for small and large wind turbines in spite of the system inertia. In fact, the optimal TSR method is being used for the practical system where both wind speed and turbine speed need to be measured for TSR calculation.

Recently, attention has been paid to improve the induction machine efficiency and transient performance. At light loads, the machine efficiency decreases due to excessive iron loss and unbalance between the copper and the iron losses. Hence energy saving can be achieved by reducing the generator flux level [4]. There is an optimal flux level which minimizes the machine loss.

In this paper a novel SVR scheme is proposed to minimize the loss of a vector controlled induction generator for wind power generation system. In this method, support vector machine for regression (SVR) estimates a continuous-valued function that plots the fundamental relation between a given input (wind speed) and its corresponding output (optimum flux current) based on the training data. This function then can be used to predict outputs for given inputs that have not been included in the training set.

A novel implementation for SVR is proposed to estimate the stator d-axis current component based on the measured wind speed to minimize the generator total loss. Experimental results are presented to

validate the proposed control algorithm.

### 2. Wind power generation system

The power captured by the wind turbine may be written as [5].

$$P_{rot} = \frac{1}{2} \rho \pi R^2 v^3 C_p(\lambda) \quad (1)$$

To fully utilize the wind energy,  $C_p$  should be maintained at  $C_{p,max}$  which is determined from the blade design. Then, from (1),

$$P_{max} = \frac{1}{2} \rho \pi R^2 C_{p,max} v^3 \quad (2)$$

The reference speed of the generator is determined from (2) as

$$\omega_r^* = \frac{\lambda_{opt}}{R} v \quad (3)$$

Once the wind velocity  $v$  is measured, the reference speed for extracting the maximum power point is obtained from (3).

### 3. Support vector machines for regression

A regression method is an algorithm that estimates an unknown mapping between a system's inputs and outputs from the available data or training data. Once such a relation has been accurately estimated, it can be used for prediction of system outputs from the input values. The goal of regression is to select a function which approximates best the system's response.

The generic SVR estimating function takes the form [6]

$$f(x) = (w \cdot \Phi(x)) + b \quad (4)$$

where the dot denotes the inner product,  $w \in R^n$ ,  $b \in R$  and  $\Phi$  denotes a non-linear transformation from  $R^n$  space to high dimensional space. The goal is to find the value of  $x$  and  $b$  such that values of can be determined by minimizing the regression risk as

$$R_{reg}(f) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n I(f(x_i) - y_i) \quad (5)$$

subject to

$$\begin{aligned} y_i - (w \cdot \Phi(x_i)) - b &\leq \varepsilon + \xi_i^* \\ (w \cdot \Phi(x_i)) + b - y_i &\leq \varepsilon + \xi_i \\ i &= 1, 2, 3, \dots, n \quad \xi_i^*, \xi_i \geq 0 \end{aligned} \quad (6)$$

where  $I(\cdot)$  is a cost function and  $C$  is a constant determining the trade-off between minimizing training errors and minimizing the model complexity term  $\|w\|^2$ . If  $C$  goes to infinitely large, SVR would not allow the occurrence of any error and result in a

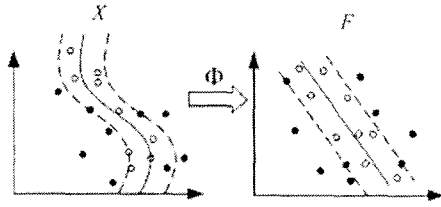


Fig. 1 A feature map from input to higher dimensional feature space

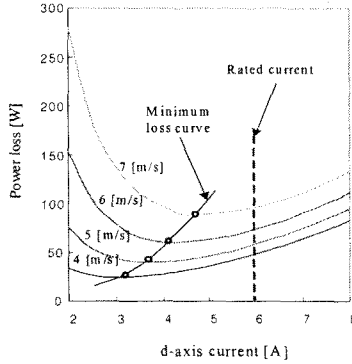


Fig. 2 D-axis current locus for minimum power

complex model, whereas when  $C$  goes to zero, the result would tolerate a large amount of errors and the model would be less complex. Everything above  $\varepsilon$  is captured in slack variables  $\xi_i, \xi_i^*$ , which are introduced to accommodate error on the input training set.

The optimization problem in (6) can be transformed into the dual problem, and its solution is given by

$$f(x) = \sum_i^n (a_i - a_i^*) \cdot (\Phi(x_i), \Phi(x)) + b \quad (7)$$

subject to  $0 \leq a_i \leq C, 0 \leq a_i^* \leq C$

In (7) the dot product can be replaced with Kernel function  $K(x_i, x)$ , known as the kernel function. Kernel functions enable the dot product to be performed in high-dimensional feature space using low dimensional space data input without knowing the transformation  $\Phi$  as shown in Fig. 1. Using a Kernel function, the required decision function will be

$$f(x) = \sum_{i=1}^n (a_i - a_i^*) \cdot K(x_i, x) + b \quad (8)$$

#### 4. Loss minimization based on SVR

Since most of the time the wind speed is lower than the rated value and the wind turbines operate at low speed and light load, the generator d-axis current can be reduced from the rated value to reduce the core loss and thereby the system efficiency is increased. By reducing the flux current level, the iron loss decreases at a given constant wind speed as shown in Fig. 2.

To apply SVR for estimating the d-axis current of the induction generator, the training data for inputs and outputs and Kernel function should be firstly specified. In this model, SVR input is the wind speed

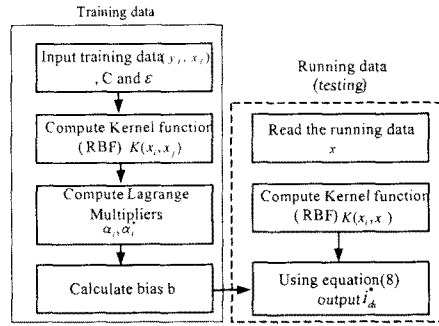


Fig. 3 Flow chart for loss minimization using SVR

while the output is the optimum value for the d-axis current, so the relation between the wind speed and d-axis current can be used as a training data and Radial Basis Function (RBF) is used as the Kernel. Training of SVR involves the off-line adjustment (training) of Lagrange multipliers and bias  $a_i$  and  $b$  in (8) respectively. During the off-line training, Kernel polynomial  $K(x_i, x_j)$  is calculated for all support vectors. Lagrange multipliers  $a_i, a_i^*$  are then determined to minimize the quadratic form

$$W(a_i, a_i^*) = \sum_{i,j=1}^n (a_i - a_i^*)(a_j - a_j^*) K(x_i, x_j) - \sum_{i=1}^n y_i (a_i - a_i^*) + \frac{1}{2C} \sum_{i=1}^n (a_i^2 - a_i^{*2}) \quad (9)$$

subject to  $\sum_i^n (a_i - a_i^*) = 0, a_i, a_i^* \in [0, C]$ .

Using Kernel polynomial  $K(x_i, x_j)$  and Lagrange multipliers  $a_i - a_i^*$ , the bias  $b$  can be computed as follow.

$$b = \text{mean} \left( \sum_i^n \{ y_i - (a_i - a_i^*) K(x_i - x) \} \right) \quad (10)$$

In order to solve this problem, one has to choose the parameters  $C$  and the value of  $\varepsilon$ . Parameters  $C$  and  $\varepsilon$  are usually selected by users based on a prior knowledge and/or user expertise.

Now, all the parameters in (8) are computed in advance off-line. Hence, (8) is used online for any input  $x$  (wind speed) to compute the output  $f(x)$  (optimum d-axis current) as shown in Fig. 3.

#### 5. Experimental results

The experimental setup has been built in a reduced-scale at laboratory, of which configuration is explained fully in [7]. A 3[kW] squirrel-cage induction generator is mechanically coupled to the dc motor without a gear box. The generator output terminals are connected to the utility grid through back-to-back converters and a transformer. In order to optimize the machine efficiency, SVR algorithm for efficiency optimization was implemented. The generator controller is based on a conventional field-oriented controller, where the flux current is maintained constant and equal to the rated value during the starting process, after that, the d-axis current is determined to optimize the generator efficiency based on SVR theory.

In SVR, the off-line training step is performed to

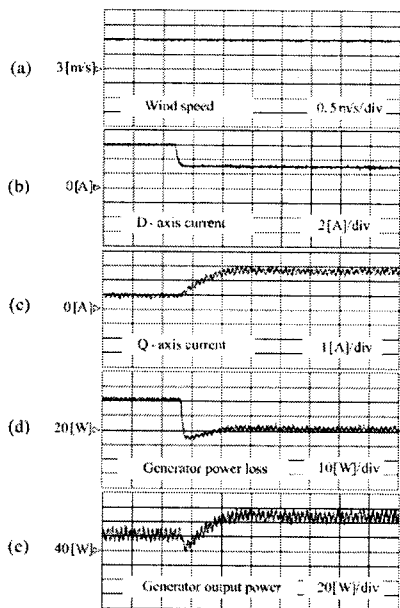


Fig. 4 Generator performance before and after applying the loss minimization at 4[m/s]

get Lagrange multipliers and bias values, and then the SVR model is available for the on-line mode. Eqs. (3) and (8) are used to calculate and estimate the generator reference speed and the generator reference d-axis current, respectively.

Figure 4 shows the generator performance at 4[m/s] wind speed. The induction generator is started with the rated flux current, and then the loss minimization algorithm is activated to calculate the reference flux current and remain active to ensure optimum efficiency operation in case of speed or torque changes. In this figure, the d-axis current is achieved at its reduced value about 3.1[A] very fast for minimum power loss. To keep the constant torque and constant speed, instead, the q-axis current is increased as shown in Fig. 4(c). The power loss is decreased from 42[W] to 22[W], it means power saving of about 45% is obtained as shown in Fig. 4(d). In the same time the generator output power increased due to loss reduction.

Figure 5 shows the reduction of the generator power loss in the low and medium speed range due to the d-axis current optimization for loss minimization. At high wind speed, the increment of the output power is negligible since the d-axis current increases up to the rated value for high torque so that there is no reduction of the iron loss. It can be seen that the improvement of the generator efficiency is not possible using the flux control at high wind speed.

Figure 6 shows the accuracy of the proposed algorithm to estimate the optimum flux current with respect to the measured current. It is obvious that SVR algorithm estimates the optimum flux current value which is almost equal to the measured optimum one.

## 6. Conclusions

In this paper, a loss minimization control scheme for wind driven squirrel-cage induction generator was

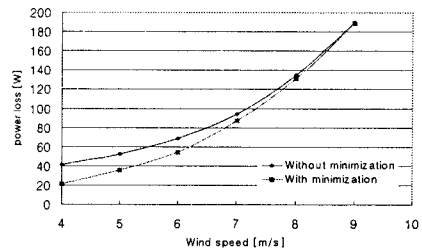


Fig. 5 Generator power loss versus wind speed

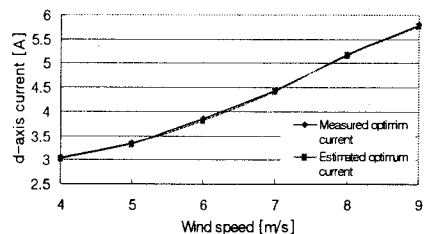


Fig. 6 D-axis current versus wind speed

proposed. The generator d-axis current was regulated to minimize the generator total losses either in constant or variable wind/generator speed, respectively. A new support vector regression algorithm to estimate the optimum value for the d-axis current based on the training data from previous off-line training was presented. The presented algorithm shows a good performance in both steady state and transient operation. This algorithm can estimate the correct value for the generator d-axis current even if the generator speed accelerates or decelerates.

"This work was supported by the Korea Research Foundation Grant Funded by the Korea Government(MOEHRD)." (KRF-2005-205B-000001)

## References

- [1] R. Leidhold, G. Garcia and M. I. Valla, "Field-oriented controlled induction generator with loss minimization", *IEEE Trans. on Ind. Electron.*, vol.49, No. 1, pp.147-156, 2002.
- [2] F. F. M. El-Sousy, M. Orabi and H. Godah, "Maximum power point tracking control scheme for grid connected variable speed wind driven self-excited induction generator," *KIPE Journal of Power Electron.*, vol. 6, No. 1, pp.45-51, Jan. 2006.
- [3] R. Hilloowala and A. M. Sharaf, "A rule-based fuzzy logic controller for a PWM inverter in a stand alone wind energy conversion scheme," *IEEE Trans. on Ind. Appl.*, vol. 32, No. 1, pp.57-65, Jan. 1996.
- [4] S. M. Yang and F. C. Lin, "Loss-minimization control of vector-controlled induction motor drives", *IEEE PEDS Conf. proc. vol. 1*, Oct., 2001, pp.182-187.
- [5] Z. Lubosny, *Wind turbine operation in electric power systems*, Springer-Verlag, 2003.
- [6] K. R. Cho, J. K. Seok and D. C. Lee, "Mechanical parameter identification of servo systems using robust support vector regression", *IEEE PESC Conf. Proc.*, Vol. 5, June 2004, pp. 3425-3430.
- [7] A. G. Abo-Khalil, H. G. Kim, D. C. Lee and J. K. Seok, "Maximum output power control of wind generation system considering loss minimization of machines", *IEEE IECON Conf. Proc. Vol. 2*, Nov. 2004, pp.1676-1681.